

Statistics: analyzing & understanding data

Common approach: use parametric model of data

Bin( $p$ ), Poi( $\lambda$ ), Exp( $\lambda$ ),  $N(\mu, \sigma^2)$ , Uni( $a, b$ )

Use  $\vec{\theta}$  to denote unknown parameters

Goal: Given indep samples  $x_1, x_2, \dots, x_n$  from parametric model, determine best choice of parameters  $\vec{\theta}$

Approach: Find MLE, most likely choice of  $\vec{\theta}$

$$L(x_1, \dots, x_n | \vec{\theta}) = \prod_{i=1}^n f(x_i | \vec{\theta})$$

likelihood  
function

density cont.  
p.m.f. cont.

$$LL(\vec{x} | \vec{\theta}) = \log(L(\vec{x} | \vec{\theta})) = \sum_{i=1}^n \log[f(x_i | \vec{\theta})]$$

log-likelihood  
function

choose  $\vec{\theta}$  to maximize  $L(\vec{x}|\vec{\theta})$

$\Leftrightarrow$  maximize  $\mathcal{L}(\vec{x}|\vec{\theta})$

1 parameter

compute  $\frac{d\mathcal{L}}{d\theta}$

set  $\frac{d\mathcal{L}}{d\theta} = 0$

Solve

verify soln is max ( $2^{\text{nd}}$  deriv  $< 0$ )

Multiple parameters

$\frac{\partial \mathcal{L}}{\partial \theta_1} = 0$

$\frac{\partial \mathcal{L}}{\partial \theta_2} = 0$

$\vdots$

$\frac{\partial \mathcal{L}}{\partial \theta_k} = 0$

check max  
Hessian -ve definite

$\frac{\partial^2 \mathcal{L}}{\partial x_i \partial x_j}$

$X_1, \dots, X_n$  samples from  $U[0, \theta]$

↑  
unknown

Find MLE of  $\theta$

$$f(x_i) = \begin{cases} \frac{1}{\theta} & 0 \leq x_i \leq \theta \\ 0 & \text{o.w.} \end{cases}$$

$$L(\vec{x} | \theta) = \frac{1}{\theta^n} \quad \text{if all } x_i\text{'s} \in [0, \theta]$$

0 otherwise

$L(\vec{x} | \theta) \downarrow$  as  $\theta \uparrow$

$$\Rightarrow \hat{\theta} = \max(x_i)$$

Estimator unbiased if

$$E(\hat{\theta}) = \theta$$

↑  
true value

We saw for mean of normal distn

$$E(\hat{\theta}) = E\left(\frac{\sum x_i}{n}\right) = \mu \quad \text{unbiased.}$$

for  $U[0, \theta]$   $\hat{\theta} = \max(x_1, \dots, x_n)$

$$E(\max(X_1, \dots, X_n)) = ? \quad \Pr(\hat{\theta} \leq x) = \prod_{i=1}^n \Pr(X_i \leq x)$$

$\downarrow$   
 $U[0, \theta]$

$$= \begin{cases} \frac{x^n}{\theta^n} & 0 \leq x \leq \theta \\ 0 & \text{otherwise} \end{cases}$$

$$f_{\hat{\theta}}(x) = \begin{cases} \frac{n x^{n-1}}{\theta^n} & 0 \leq x \leq \theta \\ 0 & \text{o.w.} \end{cases}$$

$$E(\hat{\theta}) = \int_0^{\theta} x f_{\hat{\theta}}(x) dx = \frac{n}{\theta^n} \int_0^{\theta} x \cdot x^{n-1} dx = \frac{n}{n+1} \theta$$

$\Rightarrow \hat{\theta}$  not unbiased, but it is asymptotically unbiased

$$\lim_{n \rightarrow \infty} E(\hat{\theta}_n) = \theta$$

iid observations  $X_1, \dots, X_n \sim U[\theta, \theta+1]$

Find MLE of  $\theta$

$$f_{X_i}(x_i) = \begin{cases} 1 & \theta \leq x_i \leq \theta+1 \\ 0 & \text{o.w.} \end{cases}$$

$$L(\vec{x} | \theta) = \begin{cases} 1 & \theta \leq \min x_i \leq \max x_i \leq \theta+1 \\ 0 & \text{otherwise} \end{cases}$$

Any  $\hat{\theta} \in [\max X_i - 1, \min X_i]$  equally good

consistent since  $\min X_i \rightarrow \theta$

$\max X_i \rightarrow \theta+1$

If choose midpoint  $\hat{\theta} = \frac{1}{2} [\max X_i + \min X_i - 1]$   
it's unbiased

$$E(\hat{\theta}) = \frac{1}{2} \left[ \underbrace{E(\max X_i)}_{\theta + 1 - \frac{1}{n+1}} + \underbrace{E(\min X_i)}_{\theta + \frac{1}{n+1}} - 1 \right] = \theta$$

Grade dist'n for 312

$$\left\{ \begin{array}{ll} A & \frac{1}{2} \\ B & \mu \\ C & 2\mu \\ F & \frac{1}{2} - 3\mu \end{array} \right.$$

MLE for  $\mu$  when samples are  $x_A, x_B, x_C, x_F$   
(Assume we see precise grade each person got)

$$L(x_A, x_B, x_C, x_F | \mu) = \left(\frac{1}{2}\right)^{x_A} \mu^{x_B} (2\mu)^{x_C} \left(\frac{1}{2} - 3\mu\right)^{x_D}$$

$$\log L(\vec{x} | \mu) = x_A \log\left(\frac{1}{2}\right) + x_B \log(\mu) + x_C \log(2\mu) + x_D \log\left(\frac{1}{2} - 3\mu\right)$$

set  $\frac{dLL}{d\mu} = 0$ , solve for  $\hat{\mu}$

$$\frac{x_B}{\hat{\mu}} + \frac{2x_C}{2\hat{\mu}} - \frac{3x_D}{\frac{1}{2} - 3\hat{\mu}} = 0$$

$$\frac{(x_B + x_C)}{\hat{\mu}} = \frac{3x_D}{\frac{1}{2} - 3\hat{\mu}}$$

$$\left(\frac{1}{2} - 3\hat{\mu}\right)(x_B + x_C) = 3\hat{\mu}x_D$$

$$\frac{x_B + x_C}{2} = 3\hat{\mu}(x_B + x_C + x_D)$$

$$\hat{\mu} = \frac{x_B + x_C}{6(x_B + x_C + x_D)}$$